DETECTION AND CLASSIFICATION OF OVARIAN TUMOR IN OBSTETRIC ULTRA SOUND IMAGING USING DEEP LEARNING

A SYNOPSIS

Submitted by

M.JEYA SUNDARI
(Reg. No. 9210004003)

in partial fulfillment for the award of the degree

of

DOCTOR OF PHILOSOPHY

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

KALASALINGAM ACADEMY OF RESEARCH AND EDUCATION

(DEEMED TO BE UNIVERSITY)

ANAND NAGAR, KRISHNANKOIL – 626126

TAMILNADU, INDIA

JUNE 2024

1. INTRODUCTION

Ovarian cancer is a significant health concern globally, often diagnosed at advanced stages when treatment options are limited. Early detection is crucial for improving survival rates, yet the disease lacks effective screening methods due to its subtle symptoms and anatomical location. However, advancements in medical technology, particularly in imaging techniques like transvaginal ultrasound and serum biomarker testing, hold promise for enhancing early detection efforts. Transvaginal ultrasound (TVUS) is one of the primary imaging modalities used in ovarian cancer detection. It allows healthcare providers to visualize the ovaries and detect any abnormalities such as tumors or cysts. While TVUS is relatively non-invasive and widely accessible, its effectiveness as a standalone screening tool is limited by its inability to distinguish between benign and malignant growths with high accuracy. As a result, it is often used in combination with other diagnostic tests.

Serum biomarker testing is another approach employed in ovarian cancer detection. Biomarkers such as CA-125 and HE4 have shown potential for identifying ovarian cancer at early stages when used in conjunction with imaging studies like TVUS. These blood tests measure the levels of specific proteins associated with ovarian cancer, providing valuable information to aid in diagnosis and monitoring. However, biomarker testing also has limitations, including variability in biomarker levels among individuals and conditions unrelated to cancer that can affect results. The integration of multiple diagnostic modalities, including imaging and biomarker testing, offers a more comprehensive approach to ovarian cancer detection. This multimodal strategy aims to improve sensitivity and specificity, reducing the likelihood of missed diagnoses or false positives. Additionally, ongoing research continues to explore novel biomarkers and imaging techniques that may further enhance early detection capabilities and inform personalized treatment approaches.

Despite these advancements, challenges remain in the early detection of ovarian cancer. The disease often presents with vague symptoms or none at all in its early stages, making it difficult to diagnose until it has progressed. Moreover, barriers such as cost, access to healthcare, and patient compliance can impact the implementation of screening

programs and delay diagnosis. Addressing these challenges requires a multifaceted approach involving healthcare providers, researchers, policymakers, and the community to improve awareness, access to screening, and the development of innovative diagnostic tools. Hence, early detection plays a critical role in improving outcomes for ovarian cancer patients. While current screening methods have limitations, ongoing research and technological advancements hold promise for enhancing detection capabilities. By adopting a multimodal approach and addressing existing challenges, we can advance early detection strategies and ultimately reduce the burden of ovarian cancer on individuals and society.

1.2. Objective of the research

The objective of this research is to develop an effective method for the early detection of ovarian tumors, a common and serious gynecologic malignancy, using advanced image processing techniques. Ovarian tumors often remain undetected until advanced stages, complicating treatment and reducing survival rates. Moreover, tumor heterogeneity contributes to poor treatment response and adverse prognosis. This study aims to utilize supervised learning for image categorization, leveraging labeled training images to achieve optimal representation and facilitate accurate clustering and classification. In particular, histopathological images will be employed to identify ovarian epithelial tumors at an early stage, enhancing diagnostic accuracy and potentially improving treatment outcomes. Additionally, ultrasound imaging techniques are considered for detecting ovarian tumors during pregnancy, further broadening the diagnostic scope. The significant objectives of three different phases are mentioned below.

- To develop an intelligent image enhancement with deep learning-based ovarian tumor diagnosis (IEDL-OVD) model thereby enhancing the quality of input medical images, thereby improving diagnostic outcomes.
- To propose a novel algorithm for multiclass ovarian tumor detection, utilizing a three-dimensional convolutional neural network-based modified bidirectional long short-term memory with pelican optimization (3D CNN-based MBiLSTM with PO).

- To identify ovarian epithelial tumors at an early stage using histopathological images and to develop an innovative and intelligent method, termed Transfer Learning with ResNet-based Deep Learning for Ovarian Tumor Detection (TLOD) thereby enhancing the accuracy and effectiveness of ovarian tumor detection.

1.3. State of art

Ovarian tumors, a prevalent gynecologic malignancy, necessitate effective image processing techniques for accurate diagnosis. Current state-of-the-art methods in machine learning for image categorization typically rely on supervised learning, utilizing labeled training images to optimally represent the data, thereby facilitating precise clustering and classification. Advanced techniques have shown promise in enhancing diagnostic accuracy. In rare instances, ovarian tumors are detected during pregnancy through ultrasound imaging, although this is not the norm. Despite advancements, ovarian tumors often remain undetected until advanced stages, complicating treatment and significantly reducing survival rates. Additionally, tumor heterogeneity presents a major challenge, leading to poor treatment responses and adverse prognoses. This research aims to address these challenges by developing a method to identify ovarian epithelial tumors at early stages using histopathological images, leveraging state-of-the-art deep learning techniques to improve diagnostic accuracy and clinical outcomes.

1.4. Problem statement

Ovarian tumors represent a significant health concern, being among the most prevalent gynecologic malignancies. Despite advancements in medical technology, accurate and timely diagnosis of ovarian tumors remains a challenge. Often, these tumors go undetected until they reach advanced stages, leading to complex treatment protocols and diminished survival rates for affected individuals. Additionally, the heterogeneous nature of ovarian tumors complicates diagnosis and treatment, as different tumor subtypes may exhibit varying behaviors and responses to therapy. Therefore, there is a

pressing need for improved detection methods that can identify ovarian tumors at early stages, enabling prompt intervention and potentially improving patient outcomes.

In the realm of medical imaging, particularly in the field of machine learning, supervised learning approaches have been commonly utilized for image categorization tasks. These methods rely on labeled training images to learn patterns and features characteristic of different classes, enabling the algorithm to classify new images accurately. However, applying these techniques to the diagnosis of ovarian tumors presents its own set of challenges. The scarcity of labeled data for rare conditions like ovarian tumors, coupled with the intricate nature of tumor pathology, makes it difficult to achieve optimal diagnostic performance using traditional machine learning approaches alone. Furthermore, the complexity of ovarian tumor heterogeneity adds an additional layer of difficulty, requiring more sophisticated methods to capture and interpret the diverse characteristics of different tumor subtypes.

To address the limitations of current diagnostic approaches and meet the urgent need for improved ovarian tumor detection, this research aims to develop innovative image processing and deep learning techniques. By leveraging advances in deep learning, particularly convolutional neural networks (CNNs) and transfer learning, this study seeks to enhance the accuracy and efficiency of ovarian tumor diagnosis. Specifically, the research focuses on utilizing histopathological images, which provide valuable insights into the cellular and tissue characteristics of ovarian tumors.

2. LITERATURE SURVEY

Wang et al. [1] introduced a convolution neural network-based deep learning approach applying magnetic resonance imaging to differentiate malignant and benign lesions at the ovary. Totally 445 lesions of 451 sufferers were considered for evaluation and split into sets of validation, testing, and training in the ratio 2:1:7. The performance of the model was compared with 3 senior-level and 4 junior-level radiologists. By the probabilities of artificial intelligence, the junior-level radiologists showed greater specificity ($p = 0.005$, $\Delta = 0.11$, 0.81 vs 0.70), the same accuracy ($p=0.409$, $\Delta = 0.03$, 0.77 vs 0.74), and ($p = 0.097$, $\Delta = -0.146$, 0.69 vs 0.83) sensitivity in comparison with senior level radiologists. However, the bias in selection could have occurred in this model.

Christiansen et al. [2] developed deep neural networks (DNNs) to differentiate malignant and benign ovarian tumors and also to contrast the accuracy of diagnosis with subjective assessment (SA) by using analysis of computerized image of ultrasound. Totally 3077 images of ultrasound of 758 females having ovarian tumors were considered for evaluation and the dataset was divided into sets of validation, testing, and training in the ratio 50:75:254. Mobile Net, ResNet50, and VGG16 were the 3 pre-tuned types of DNA. The ensemble DNN categorized the tumors under model Ovry-Dx1 and model Ovry-Dx2 and they showed specificity and sensitivity in comparison with SA. Conversely, there were limitations in generalization and the deployment of multisite potential.

Mathur, M. and Jindal, V., [3] implemented a deep convolution neural network to recognize ovarian cancer by utilizing histo pathological pictures. CNN's model DenseNet-201 was utilized for the extraction of features. For the classification of benign and malignant types of cancer, the dataset called PLCO was utilized with achieved high accuracy of 94.73, F1-score 0.95, precision of 0.91, and recall of 1.00. The method showed better reorganization performance. Rather, this method was not validated with a large set of data.

Taleb et al. [4] implemented K-Nearest Neighbor (KNN) and Support vector machine (SVM)- machine learning algorithms to detect ovarian cancer. First, the data were

standardized and optimized. The SVM obtained 97.16% and 98.1% of accuracy in validation and training respectively. The accuracy was improved when utilized in the systems of clinical diagnosis and produced an improvement in the survival rates of patients. However, more data on patients were needed for the prediction of ovarian cancer.

Yin et al. [5] implemented deep learning approaches depending on the images of contrast-enhanced CT (CECT) to predict the response of NACT and to classify high-grade serous ovarian cancer (HGSOC). Totally 757 patients were considered for evaluation, and 1761 images of 587 females in validation and training sets 201 images of 67 females in expected sets, and 309 images of 103 females in exterior sets. By the analysis of Logistic regression, it was found that the AUCs for the exterior, expected, validation, and training sets were 0.789, 0.86, 0.88, and 0.87 respectively. The outcome showed better prediction and classification performance. However, this method extended the staying time of the tumor.

Zheng et al. [6] established a combined radiomic and clinical features approach to nondamaging differentiation of malignant and benign solid types of ovarian tumors. 148 sufferers with 156 solid types of ovarian tumors were considered and divided into tests and training set in the ratio 2:8 through layered irregular sampling. Through the least absolute shrinkage and selection operator(LASSO), 12 and 1612 clinical and radiomic characteristics were separated. The models of radiomic, clinical, and integrated achieved better differentiating performance with 0.714, 0.909, 0.839, and 0.954($p<0.01$, CI 95%, 0.862-1.0) of sensitivity, precision, accuracy, and AUC respectively. Rather, this method did not evaluate the radiologists' accuracy.

Kodipalli et al. [7] introduced a deep convolutional neural network to classify ovarian tumors through the images of CT. An advanced ImageNet Large Scale Visual Recognition Challenge (ILSVRC) designs comparison for ovarian tumors classification by evaluating and training images over the ovarian images of CT scan by use of Google Cloud Platform. This design achieved 97.53% accuracy and beat other variants of CNN. Nevertheless, this method used less number of samples which led to the problem of overfitting.

Kongara et al. [8] introduced a krill herd optimization-based convolutional neural network (KHO-CNN) method, an approach of the deep neural network to detect ovarian tumors. The ovarian cancer detected by ultrasound was considered as a dataset. The extra noise was eliminated by Wavelet Transform. Utilizing local binary arrangement, characteristics were separated. By utilizing KHO-CNN, the tumors were categorized into normal malignant, and benign. By utilizing CNN, the ovarian cancers were identified. Rather, this method needed the best features for detection.

Feng, Y., [9] established a machine learning model for diagnosis and artificial neural network categorizers for the development of medical routine indexes of blood for helping ovarian cancer diagnosis. 185 sufferers having ovarian cancer and other 3 sufferers groups were taken for evaluation. An automated network of segmentation was implemented to enhance the results of segmentation reproducibility. The pre-tuned Res Net50 was used for the fusion of three corner outcome modules. The machine learning model of diagnosis' ROC curve attained 0.948, together with 86.9% specificity, and 91.9% sensitivity. Yet, the accuracy of diagnosis was required to be improved.

Wu et al., [10] developed a strong signature of prognosis on the basis of features of blood for the prediction of prognosis and enhanced ovarian cancer (OC) output. Among 331 patients having OC, blood characteristics of 33 and age were screened. Through 10 machine learning programs, 88 mixtures, and 1 were chosen for blood risk score (BRS) construction. The best performance was obtained from (alpha=0.7) Enet and (both)Stepcox in the dataset of testing with 0.711 C-index. This model produced greater values of AUC at the years of 7, 3, and 5. The method showed better prediction performance. Still, the exterior validation was not performed.

Ravishankar et al., [11] introduced ovary cyst detection through fuzzy rule-dependent Convolutional Neural Network (OCD-FCNN) for the detection of cysts in the ovarian and categorization. This method produced an accurate outcome of 98.37% by using the standard datasets. For testing and training, respectively 120 and 320 images were utilized to decrease the delay in computation. This method provided an exact diagnosis of the illness. Rather, the sequential constraints were not used.

Aelgani and Vadlakonda [12] introduced a standardized convolutional neural network (CNN) together with an altered transformer XLNet for dividing and classifying ovarian cancer. From the internet source, the dataset was collected. Adaptive Gaussian Filter and the strategy of Adaptive Weighted Guided Image Filtering with a Siberian Tiger Optimization (STO) were used for pre-processing of gathered images. After ovary segmentation, feature separation was done on the basis of RGB-dependent 3-channel characteristics. For a feature in visual separation, altered transformer XLNet was utilized. At last, Gradient-weighted Class Activation Mapping (Grad-CAM) was implemented for efficient classification.

Narmatha et al., [13] established deep reinforcement learning with Harris Hawks Optimization (HHO), a convolution neural network (CNN) method for the detection of cysts in the ovary by utilizing images of cysts from a database that was ongoing. First noise was removed by preprocessing and then features separation, after that classification was done using the DRL-HHO classifier. For Q-network training, Deep Q-network (DQN) was implemented. The hyper parameters were optimized by utilizing an optimization approach. Therefore, the HHO-DQN showed better cyst categorization performance.

Suganya et al., [14] developed a deep learning neural network (DLNN) method for the classification and detection of cysts in the ovary. First, the cysts in the ovary were pre-processed for quality enhancement. The feature Haralick, histogram of color, and moments of Hu were the features that separated the Inception structure of the DLNN method to achieve different masses. At last, an extreme gradient boosting (XGBoost) categorizer was employed for to identification process. The outcome showed 98% accuracy on detection.

Fan et al., [15] established a deep learning network to diagonalizable and classify the cysts in the ovary, called Ocys-Net. The worldwide data were used for the potential of feature separation. The module of efficient channel attention (ECA) was utilized for the realization of domestic cross-channel communication, which compensated for the defects by reducing channel size and paying attention to features of pathological data. The performance of this learning network was evaluated by the dataset of cysts with accuracy

at high. Therefore, 95.93% of accuracy on this classification was obtained. However, there was no identification of more kinds of cysts in the ovary.

3. PROPOSED METHODOLOGY

By employing supervised learning techniques on histopathological images, the study aims to detect ovarian epithelial tumors at an early stage. Early detection is crucial in improving patient outcomes, as it allows for prompt intervention and treatment. Additionally, accurate identification of tumors can lead to more tailored and effective treatment strategies, potentially resulting in better treatment outcomes for patients affected by ovarian cancer. Overall, the study aims to enhance diagnostic accuracy and ultimately contribute to improved treatment outcomes for individuals diagnosed with ovarian epithelial tumors. The overall workflow depicting three vital phases of this research is illustrated in Figure 1.

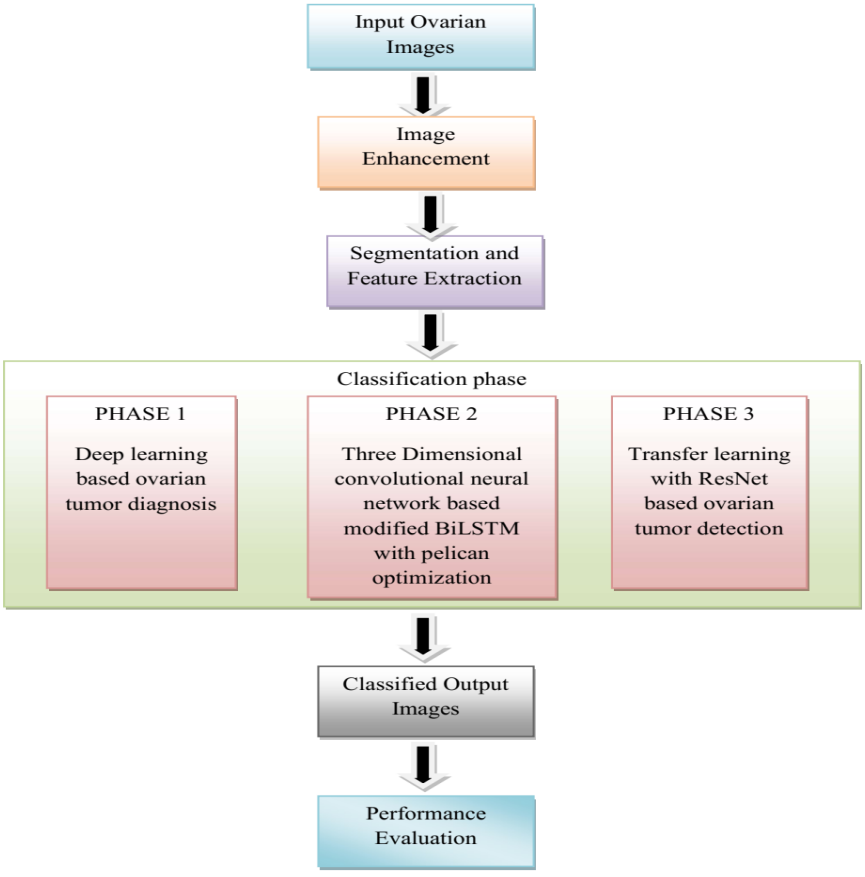

Figure 1: Overall architecture

Phase 1: An Intelligent Model for Ovarian Tumor Diagnosis Using Image Enhancement with Black Widow Optimization and Deep Learning

Phase 1 introduces an innovative approach called the Intelligent Image Enhancement with Deep Learning-Based Ovarian Tumor Diagnosis (IEDL-OVD) model. The primary objective of the IEDL-OVD model is to improve the quality of medical images used for diagnosing ovarian tumors, ultimately enhancing diagnostic outcomes. To achieve this goal, the proposed model combines several advanced techniques, including black widow optimization-based image enhancement (IE), the VGG16 model as a feature extractor, and a stacked autoencoder (SAE) for classification. The first component of the IEDL-OVD model is the black widow optimization-based image enhancement technique. This optimization approach aims to enhance the quality and clarity of the input medical images, making it easier for subsequent analysis and diagnosis. By optimizing image features and enhancing relevant details, this technique contributes to improving the overall diagnostic accuracy of the model. Additionally, the VGG16 model is employed as a feature extractor within the IEDL-OVD framework. The VGG16 model is a pre-trained convolutional neural network (CNN) known for its effectiveness in extracting high-level features from images. By leveraging the feature extraction capabilities of the VGG16 model, the IEDL-OVD model can capture important visual patterns and characteristics indicative of ovarian tumors.

Furthermore, the IEDL-OVD model utilizes a stacked autoencoder (SAE) as a classification model to determine the presence of ovarian tumors. SAEs are a type of artificial neural network used for unsupervised learning, where the network is trained to reconstruct its input data. In the context of the IEDL-OVD model, the SAE acts as a powerful classifier, leveraging the extracted features from the VGG16 model to accurately classify medical images as either containing or not containing ovarian tumors. To evaluate the diagnostic performance of the IEDL-OVD model, comprehensive experimentation analysis is conducted. This involves assessing the model's performance using various evaluation parameters, such as accuracy, sensitivity, specificity, and area under the curve (AUC). By thoroughly examining the results across these metrics, the study provides a comprehensive understanding of the effectiveness and reliability of the proposed IEDL-OVD model in diagnosing ovarian tumors.

Phase 2: Factorization-Based Active Contour Segmentation and Pelican Optimization-Enhanced Modified Bidirectional Long Short-Term Memory for Ovarian Tumor Detection.

Phase 2 presents an innovative algorithm for detecting multiclass ovarian tumors by combining a three-dimensional convolutional neural network (3D CNN) with a modified bidirectional long short-term memory (MBiLSTM) model, enhanced by pelican optimization (PO). The study begins with the preprocessing of images from the International Collaboration on Cancer Reporting (ICCR) endometrial cancer dataset. In this phase, a pre-emphasis filter is applied to the images, which enhances certain features by amplifying high-frequency components, making the significant details more prominent for further analysis. In the segmentation phase, the preprocessed images are divided into smaller segments or pixels, effectively reducing the complexity of the images. This segmentation is achieved using a factorization-based active contour technique, a method that accurately delineates the boundaries of objects within the images by iteratively refining a curve to fit the contours of the tumors. This step is crucial for isolating the relevant features from the background, enabling more precise feature extraction.

The segmented features are then processed through the 3D CNN-MBiLSTM with PO algorithm for classification. The 3D CNN is adept at capturing spatial features in three dimensions, which is particularly useful for analyzing medical images. The MBiLSTM, a type of recurrent neural network, processes the extracted features by considering both past and future context, enhancing temporal feature recognition. The pelican optimization algorithm further fine-tunes the model parameters, ensuring optimal performance. The experimental results demonstrate the algorithm's effectiveness, with performance metrics showing significant improvements compared to other methods, indicating its potential for accurate and efficient multiclass ovarian tumor detection.

Phase 3: Transfer Learning with ResNet for Accurate Multiclass Classification in Ovarian Tumor Detection and Clinical Application

In phase 3, an innovative method called Transfer Learning with ResNet-based Deep Learning for Ovarian Tumor Detection (TLOD) has been developed to identify ovarian

epithelial tumors at a premature stage using histopathological images. This method addresses the critical need for improved ovarian tumor detection to enhance early diagnosis and patient outcomes. The core innovation of TLOD involves modifying the final classification layers of a standard residual network (ResNet) by incorporating dense blocks. These dense blocks enable the merging and passage of extracted features, facilitating the multi-classification of ovarian tumors. This advanced approach equips medical professionals with a more accurate diagnostic tool, potentially revolutionizing early detection practices and improving survival rates among patients. The histopathological images used in this research are sourced from the National Cancer Institute Genomic Data Commons Data Portal, ensuring a high-quality dataset for analysis. To manage the variations in the input data, the images undergo a preprocessing pipeline that includes resizing and intensity standardization. These preprocessing steps are crucial in normalizing the data, making it suitable for deep learning algorithms. Additionally, to enhance the robustness and generalization capability of the model, data augmentation techniques are employed to expand the size of the training dataset. This augmentation process includes transformations such as rotation, flipping, and scaling, which help the model learn from a more diverse set of images, thereby improving its ability to generalize to new, unseen data. The training of the TLOD model is meticulously optimized by manipulating control parameters like batch size, learning rate, and momentum using a Stochastic Gradient Descent (SGD) optimizer. This optimization process is critical in achieving the best possible performance from the model. The TLOD technique has demonstrated remarkable efficacy, achieving an overall multi-class ovarian tumor detection performance of 98.82%. This high accuracy underscores the reliability and efficiency of TLOD as a tool for early ovarian tumor detection. By providing a highly accurate detection method, TLOD holds significant promise for enhancing diagnostic precision in clinical settings, thereby improving the overall prognosis and treatment outcomes for patients with ovarian epithelial tumors.

4. Experimental Results

The experimental analysis to evaluate the effectiveness of the developed models is performed in this section. Ovarian tumors are a serious disease affecting women's health, reducing survival rates since it does not detect until they attain advanced levels. Thus, a

successful detection model is mandatory to gain effective detection output with minimum time. Here, three phases are presented in this section, comprising several graphical representations to substantiate the performance of the phases in detecting ovarian tumors. Each phase clarifies the performance of the detection model with the use of evaluation metrics. The comparative analysis is carried out to demonstrate which phase is more robust than the other two phases. The performance of the phases is verified through specificity, precision, recall, accuracy, sensitivity, and F1-score. These measures guarantee the efficiency of the phases in diagnosing Ovarian tumors. The evaluation of the phases is specified as follows:

4.1 Evaluation Parameters

The performance is gauged through different evaluation measures such as precision, F1-score, recall, specificity, AUC-ROC, and accuracy.

1. **Specificity**: It is the proportion of correctly predicted negative images to all actual negative images
2. **Accuracy**: It is the ratio of accurately detected images to the total number of images in the dataset.
3. **Recall**: It measures the method's ability to correctly detect positive images, which is the rate of accurately predicted positive images to all actual positive images
4. **F1-score**: It is utilized when there is an imbalance in the dataset and it is defined as the harmonic mean of precision and recall.
5. **Precision:** The rate of correctly predicted positive images to all images predicted as positive is called precision.

4. 2.1 Phase 1 Analysis

The overall performance estimation of phase 1 is illustrated in this section with some performance metrics through graphical illustrations. Figure 2 presents the graphical analysis of efficiency for phase 1 with respect to accuracy, sensitivity F1-score, specificity, and precision. It reveals that the higher effectiveness for phase 1 is attained in each measure. Firstly, the accuracy for Phase 1 seems greater, i.e., 97.8%, which confirms that the positive and negative cases are identified correctly in Phase 1. The sensitivity for phase 1 procures 96.2% in the detection of Ovarian tumors. This proves that the positives are accurately identified in phase 1 by achieving a higher Sensitivity of

96.2%. The F1-score performance for phase 1 gains higher at 97%, which confirms that the misclassifications are minimized by balancing between both parameters. The performance based on precision for phase 1 reaches a higher, which gains a maximum of 97.2%. This implies that the tumors are predicted correctly in phase 1. Specificity of the phase 1 is 95.5 in the graphical analysis, demonstrating that the healthy cases are not misclassified as positive. The overall performance for phase 1 ensures that it performs well in identifying the ovarian tumor.

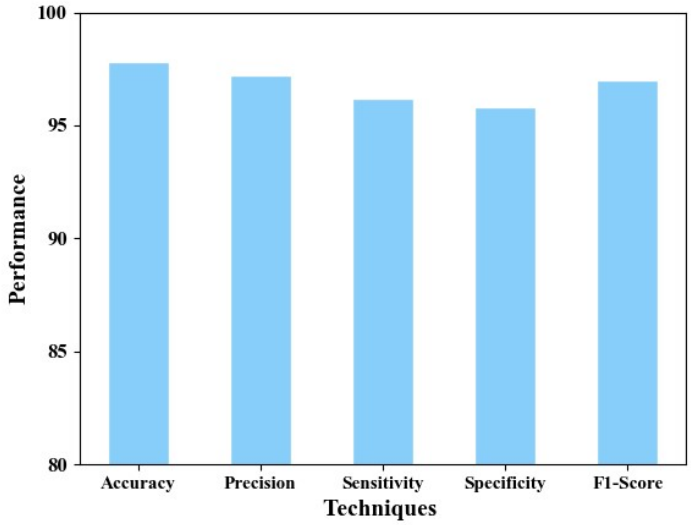

Figure 2: Efficiency of the ovarian tumor detection based on several parameters

Figure 3 illustrates the ROC analysis for phase 1 including the false positive rate and true positive rate. The ROC analysis for Ovarian tumor detection could bestow the comprehensive evaluation in various thresholds. Phase 1 furnishes a maximum of 0.981 AUC, which implies better classification ability in differentiating between non-tumor cases and ovarian tumor cases. The ROC analysis for Phase 1 proves that the Ovarian tumor has been identified successfully.

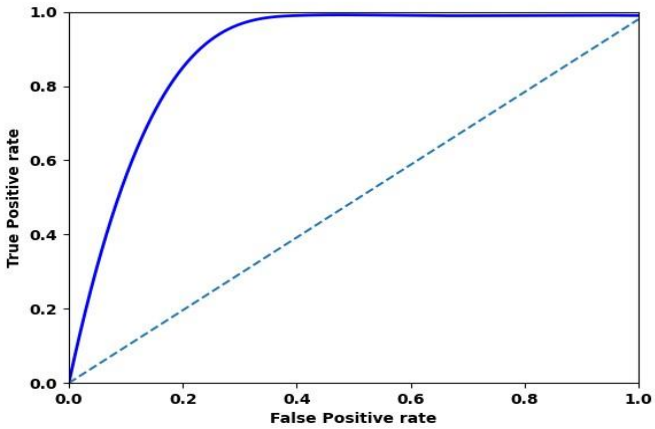

Figure 3: ROC Curve for Ovarian Tumor Detection

The graphical illustration of the execution time is represented in Figure 4. It encompasses time estimation to detect the predictions related to the presence or absence of ovarian tumors. The graphical analysis states that Phase 1 provides optimal detection results since it consumes less time. In Phase 1, the lower execution time is applied in detecting tumors, which reveals that the tumor detection process has been accomplished more quickly in Phase 1. Thus, reduced execution time allows physicians to obtain prompt results and take quick action and also it reduces energy consumption. The execution time is estimated for each iteration in the graph, in each iteration less time is deployed for Phase 1.

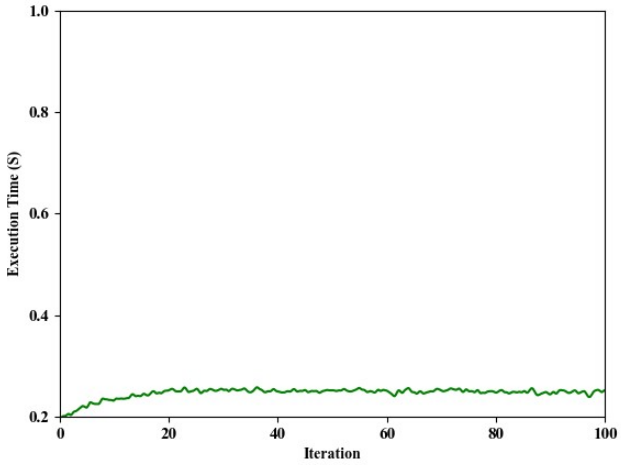

Figure 4: Execution Time Analysis for Ovarian Tumor Detection Pipeline

4.2.2 Phase 2 Analysis

The capability to identify the ovarian tumor is to be gauged for Phase 2 in this section. As specified in the above section, a few evaluation parameters such as F1-score, Precision, specificity, and sensitivity are exploited are illustrated in Figure 5, which verify the efficiency of detecting ovarian tumors. In the graphical analysis, higher F1-score, specificity, precision, and sensitivity are attained in phase 2. This means that the positive and negative cases of ovarian tumors are differentiated accurately. A higher specificity of 98.25% is reached in Phase 2, high specificity rates note that the low false positive rates are identified rightly. The F1 score for phase 2 is 96% in detecting ovarian tumor prediction. A high F1-score of Phase 2 signifies the lower false negatives and false positives for the classification of ovarian tumors. The positive classes are identified from each and every true positive class in phase 2 by gaining a higher F1 score and perfectly balancing the precision and sensitivity. Using sensitivity, the rate of the actual positive classes is calculated. The true positive class of ovarian tumors is identified by lowering the false negative rate; the sensitivity reaches 97 % in phase 2. Then, the precision rate for phase 2 is 97.5%, which procures higher efficiency in the detection of ovarian tumors. The accuracy for phase 2 is 98.6%, its higher accuracy denotes that ovarian tumor is identified timely with high accuracy. The comprehensive analysis of greater F1-score, precision, specificity, and sensitivity illustrates that the ovarian tumor is predicted precisely in phase 2.

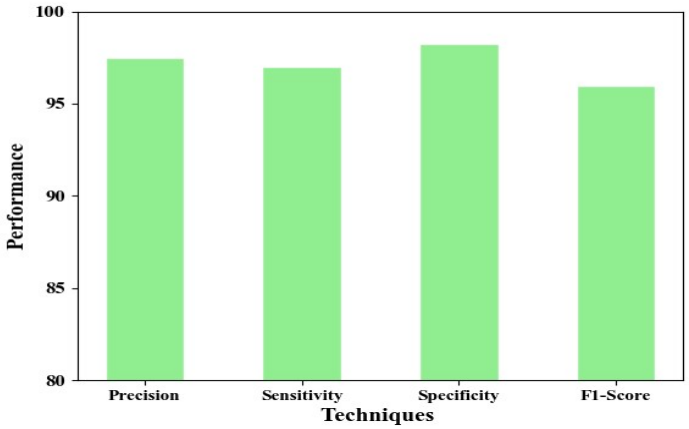

Figure 5: Efficiency estimation using some performance metrics

The ROC's graphical representation is represented in Figure 6. The graph plots the false positive rate and true positive rate with several values for Phase 2. As specified the ROC distinguishes false positive rates and true positive rates, this estimation ensures the higher and satisfactory performance. 0.982 AUC value are reached for Phase 2, which denotes that the model can effectively classify the patients with ovarian tumors. In the context of ROC analysis, phase 2 gains efficacious efficiency to discover ovarian tumors.

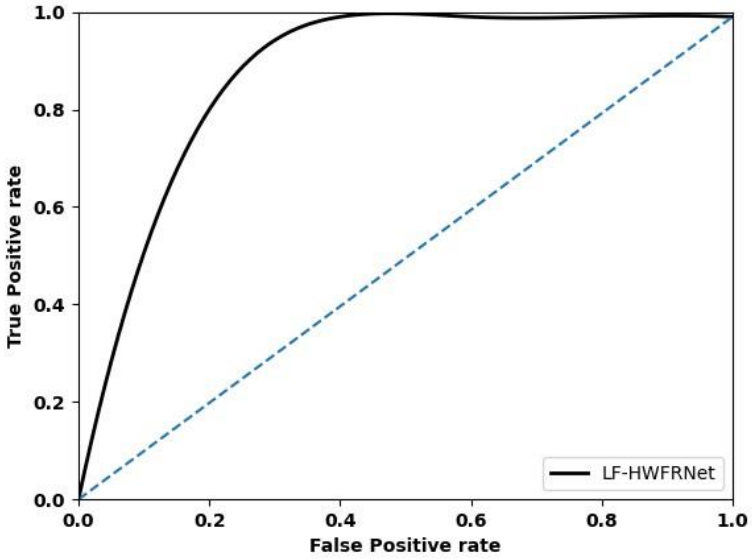

Figure 6: Performance evaluation based-ROC

Time estimation to ensure that the model is superior in detecting ovarian tumors is important. So, execution time needs to be calculated to demonstrate the detection ability. The time exploited to attain the prediction results in phase 2 is demonstrated in Figure 7. When the time increases in processing images by segmentation and feature extraction the efficiency will reduce. In this context, the low time for execution is applied for phase 2. In each iteration, the time spent is specified, phase 2 has the advantage of using time in detection. From iteration 20 to 100, time is denoted in the graphical analysis.

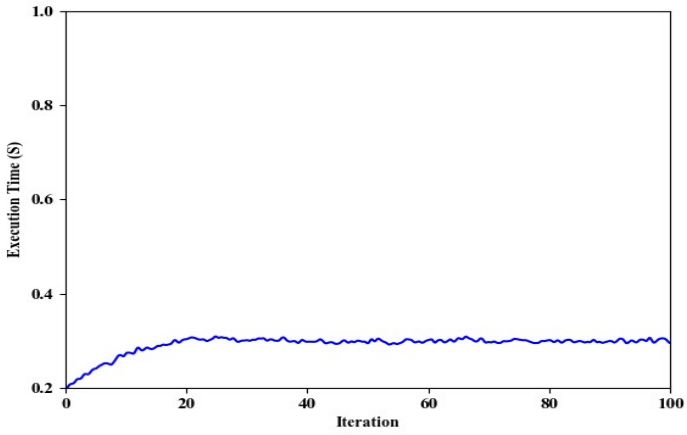

Figure 7: Time analysis for ovarian tumor prediction

4.2.3 Phase 3 analysis

A comprehensive analysis to confirm the efficiency of phase 3 is elucidated graphically. With the graphical analysis for phase 3, we can determine the performance in discovering the ovarian tumor. Estimating performance utilizes some evaluation measures namely specificity, precision, accuracy, recall, and f1-score. Figure 8 provides a performance graph in terms of these measures. The performance based on each measure is implied in Figure. Higher f1-score, accuracy, precision, specificity, and recall are achieved to find ovarian tumors. In Phase 3, the F1 score reaches a maximum rate of 97.8, The greater F1 score points out that striking the perfect balance between sensitivity and positive predictive value. This balance is crucial because misclassifying tumors as benign can have significant consequences for patient outcomes. In the graph, the accuracy of 99% is acquired for the Phase 3. When accuracy achieves maximum, correct predictions are made; it encompasses the holistic consideration of correctly classifying both tumor and non-tumor cases. The precision of Phase 3 is 97.4% in detecting ovarian tumors. This precision is crucial in preventing unnecessary anxiety and treatments for patients who do not have ovarian tumors. A predictive model with high precision minimizes the number of false positives. Based on this, the prediction performance based on the precision rate is greater in phase 3. Next, the specificity for phase 3 is greater, i.e., 97.8%, which gives better efficiency to the detection of ovarian tumors. By minimizing false positives, specificity ensures that the predictive model accurately identifies patients without ovarian tumors. Following this, the recall rate for the Phase is exhibited as

higher, 96.2% is attained recall rate in the phase. A high recall ensures that the predictive model detects the majority of actual tumor cases, minimizing the risk of potentially life-threatening conditions.

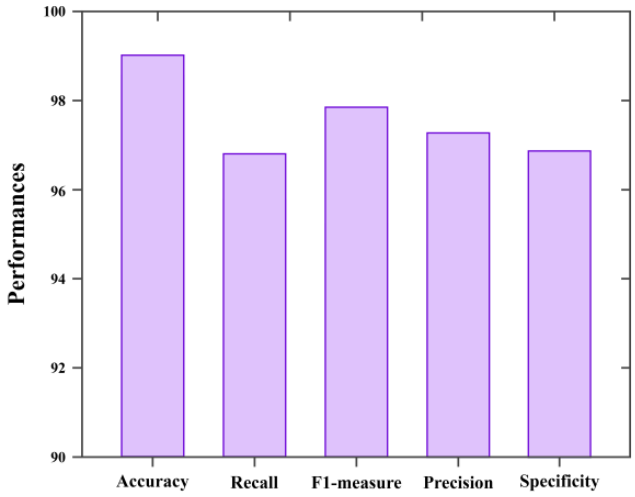

Figure 8: Graphical analysis using several evaluation measures

The ROC curve serves as a measure of robustness, quantifying the effectiveness of the predictive model in discerning true positives amidst the challenges of false positives. Figure 9 imparts the ROC graphical analysis for Phase 3. The curve illustrates the delicate balance between sensitivity and specificity, with steep inclines signifying higher accuracy in distinguishing true positives from false leads. 0.989 AUC value is reached for the phase 3.

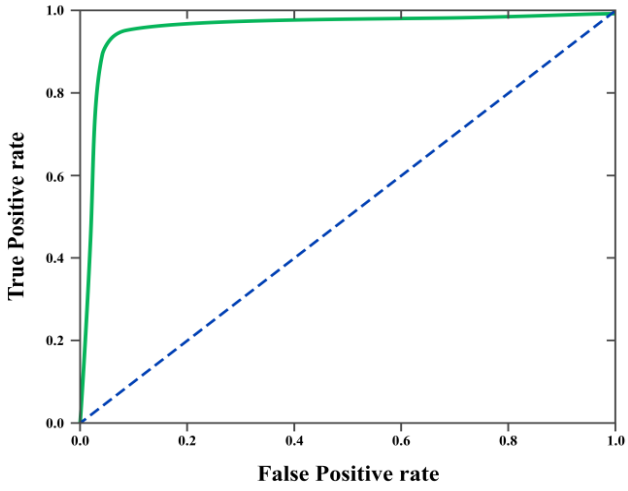

Figure 9: ROC analysis-based ovarian tumor prediction

Figure 10 represents the time estimation for Phase 3, this specifies the time taken by Phase 3 to reach appropriate outcomes. The timings are noted based on the number of iterations in the Figure. It demonstrates that phase 3 gets effective performance in time analysis, i.e., it procures lower time during the prediction of the ovarian tumor. The efficiency of execution time impacts the speed at which medical professionals can obtain diagnostic insights, potentially leading to timely interventions or treatments for patients. Optimizing execution time ensures that computational resources are utilized efficiently. Lower execution time illustrates that phase 3 enables accurate ovarian tumor detection and classification.

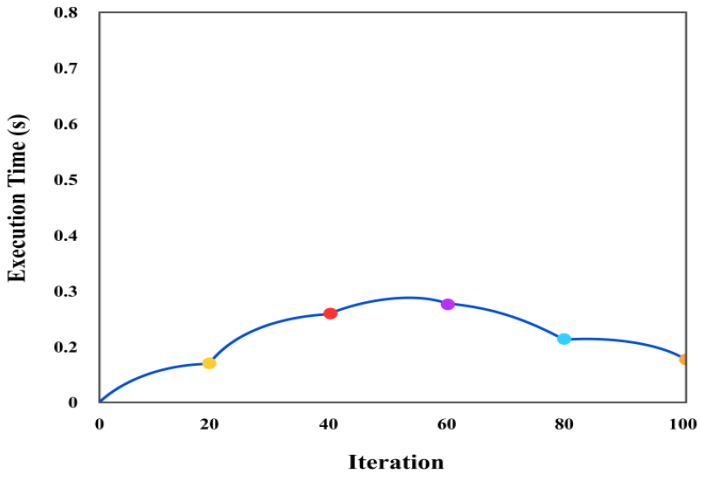

Figure 10: Execution time analysis

4.3 Comparative Analysis

This section confers the comparative analysis of the various phases such as Phase 1, Phase 2, Phase 3, and Phase 4. When comparing the performance between the phases, ensures the capability of the prediction process. The overall performance of the phases in terms of detection rate and execution time is provided in this section. Figure 11 denotes the overall performance based on the detection rate. The performance of the three phases (P1, P2, and P3) is signified, which illustrates that the P3 achieves a higher detection rate compared to the other two phases. P3 attains a detection rate of 98.9% in identifying ovarian tumors.

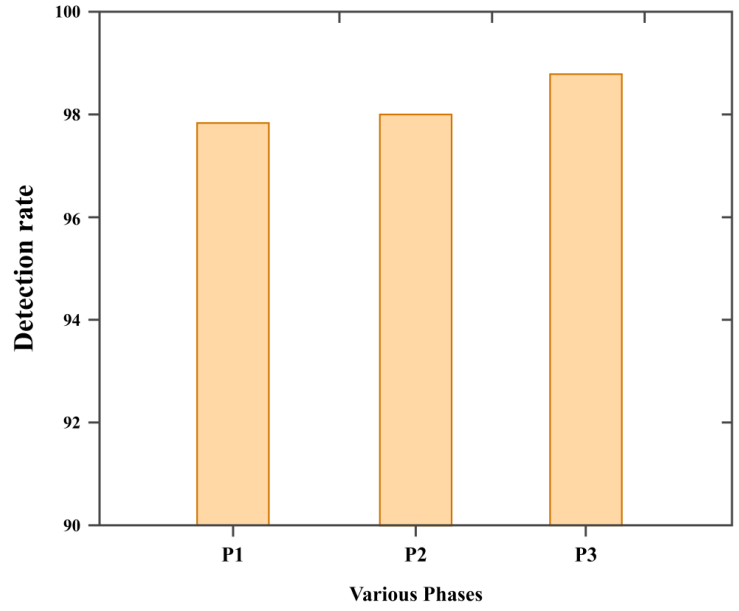

Figure 11: Detection rate for three phases

The graphical illustration of the three phases (P1, P2, and P3) with respective to ROC is indicated in Figure 12. The ROC of the P1 is a little lower than the other two phases. Among the three phases, phase 3 is the superior method in detecting ovarian tumors because it takes higher AUC values. This leads to overall greater accuracy in the detection of ovarian tumors with higher classification rates.

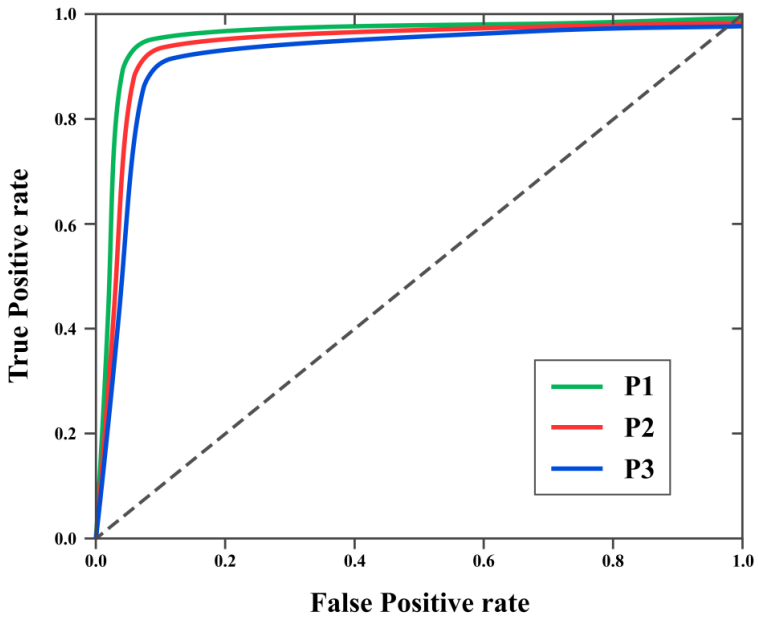

Figure 12:ROC analysis for three phases

4. 4 CONCLUSION

The advancements in predictive modeling for ovarian tumor detection present promising avenues for improving diagnostic accuracy and patient outcomes in clinical practice. Through detailed comparative analysis and evaluation of various phases, this work has elucidated the strengths and limitations of different predictive models. By identifying the most effective model, clinicians can make more informed decisions regarding patient care, facilitating timely interventions and personalized treatment strategies. accuracy, precision, recall, AUC-ROC, specificity, execution time, and detection time measures gauge the performance of the phases. Among three phases, Phase 3 provides effective results in every accuracy, precision, recall, AUC-ROC, specificity, execution time, and detection time

REFERENCES

1. Wang, R., Cai, Y., Lee, I.K., Hu, R., Purkayastha, S., Pan, I., Yi, T., Tran, T.M.L., Lu, S., Liu, T. and Chang, K., Evaluation of a convolutional neural network for ovarian tumor differentiation based on magnetic resonance imaging. *European radiology*, **31** (2021), 4960-4971.
2. Christiansen, F., Epstein, E.L., Smedberg, E., Åkerlund, M., Smith, K. and Epstein, E., Ultrasound image analysis using deep neural networks for discriminating between benign and malignant ovarian tumors: comparison with expert subjective assessment. *Ultrasound in Obstetrics & Gynecology*, **57** (1) (2021), 155-163.
3. Mathur, M. and Jindal, V., A convolutional neural network approach for detecting malignancy of ovarian cancer. In *Soft Computing and Signal Processing: Proceedings of 3rd ICSCSP 2020*, Springer Singapore.**2** (2022), 305-31.
4. Taleb, N., Mehmood, S., Zubair, M., Naseer, I., Mago, B. and Nasir, M.U., February. Ovary cancer diagnosing empowered with machine learning. In *2022 International Conference on Business Analytics for Technology and Security (ICBATS)* (2022), 1-6.
5. Yin, R., Guo, Y., Wang, Y., Zhang, Q., Dou, Z., Wang, Y., Qi, L., Chen, Y., Zhang, C., Li, H. and Jian, X., Predicting neoadjuvant chemotherapy response and high-grade serous ovarian cancer from CT images in ovarian cancer with multitask deep learning: a multicenter study. *Academic Radiology*, **30** (2023), S192-S201.
6. Zheng, Y., Wang, H., Li, Q., Sun, H. and Guo, L., Discriminating between benign and malignant solid ovarian tumors based on clinical and radiomic features of MRI. *Academic Radiology*, **30** (5) (2023), 814-822.
7. Kodipalli, A., Devi, S.V., Dasar, S. and Ismail, T., A novel variant of deep convolutional neural network for classification of ovarian tumors using CT images. *Computers and Electrical Engineering*, **109 (**2023), 108758.
8. Kongara, S.R., Prakasha, S., Brindha, A., Pathak, S.K., Miya, J., Taqui, S.N., Almoallim, H.S., Alharbi, S.A. and Raghavan, S.S., Performance evaluation of optimized convolutional neural network mechanism in the detection and classification of ovarian cancer. *Multimedia Tools and Applications*, (2024),1-24.

9. Feng, Y., An integrated machine learning-based model for joint diagnosis of ovarian cancer with multiple test indicators. *Journal of Ovarian Research*, **17** (1) (2024), 45.
10. Wu, M., Gu, S., Yang, J., Zhao, Y., Sheng, J., Cheng, S., Xu, S., Wu, Y., Ma, M., Luo, X. and Zhang, H., Comprehensive machine learning-based preoperative blood features predict the prognosis for ovarian cancer. *BMC cancer*, **24** (1) (2024), 267.
11. Ravishankar, T.N., Jadhav, H.M., Kumar, N.S. and Ambala, S., 2023. A deep learning approach for ovarian cysts detection and classification (OCD-FCNN) using fuzzy convolutional neural network. *Measurement: Sensors*, **27** (2023), 100797.
12. Aelgani, V. and Vadlakonda, D., A novel interpretable regularized cnn with a modified xlnet transformer for segmenting and classifying the ovarian cancer. *Multimedia Tools and Applications*, (2024), 1-28.
13. Narmatha, C., Manimegalai, P., Krishnadass, J., Valsalan, P., Manimurugan, S. and Mustafa, M., Ovarian cysts classification using novel deep reinforcement learning with Harris Hawks Optimization method. *The Journal of Supercomputing*, **79** (2) (2023), 1374-1397.
14. Suganya, Y., Ganesan, S., Valarmathi, P. and Suresh, T., A diagnosis of ovarian cyst using deep learning neural network with XGBoost algorithm. *International Journal of Information Technology*, **15** (7) (2023), 3499-3506.
15. Fan, J., Liu, J., Chen, Q., Wang, W. and Wu, Y., Accurate Ovarian Cyst Classification with a Lightweight Deep Learning Model for Ultrasound Images. *IEEE Access*. (2023)

LIST OF PUBLICATION

Jeya Sundari M, Brintha NC. [1] A comparative study of various machine learning methods on ovarian tumor. *2021 Sixth International Conference on Image Information Processing (ICIIP) IEEE*. **6** (2021). 314-319

Jeya Sundari M, Brintha NC. [2] An intelligent black widow optimization on image enhancement with deep learning based Ovarian Tumor diagnosis model. *Computer Methods Biomech and Biomed Eng: Imaging & Visualization*. **11** 3 (2022), 598–605.

Jeya Sundari M, Brintha NC. [3] Factorization-based active contour segmentation and pelican optimization-based modifed bidirectional long short-term memory for ovarian tumor detection. *Int J Imaging Syst Technol* **.33** 1 (2023), 230–245.

Jeya Sundari M, Brintha NC. [4] TLOD: Innovative ovarian tumor detection for accurate multiclass classification and clinical application. *Network Modeling Analysis in Health Informatics and Bioinformatics*. **13** 1 (2024), 18.